The Cognitive Consequences of Childhood Adversity: An Investigation of Feedback Learning Strategies and the Sensitized-Specialization Hypothesis

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Abstract

Stressful environments have a profound impact on children. The prevailing view is that adverse experiences in childhood impairs the mind and derails development. In contrast, the current research draws on the *specialization hypothesis*, which proposes that children should develop specialized cognitive abilities that are adapted to adverse environments. This view focuses on the strengths of people who have experienced adversity instead of exclusively on their weaknesses. In this dissertation, I test how different learning abilities might be enhanced by exposure to early adversity. I conducted four experimental tests of this hypothesis in relation to reversal learning performance, examining how growing up in unpredictable versus predictable environments are associated with different learning strategies. I hypothesize that growing up in a more predictable environment should be associated with the use of learning strategies that integrate information over longer periods of time, whereas growing up in a more unpredictable environment should be associated with learning strategies that rely on recent information. Furthermore, based on previous studies, I hypothesize that such learning strategies should be activated by the threat of uncertainty in the current environment. Across 4 experiments, I tested how exposure to childhood unpredictability impacts both overall reversal learning performance and trial-by-trial learning styles and tested whether current, experimentally manipulated cues of economic uncertainty modulated reversal learning outcomes. Findings were mixed and inconsistent. On average, overall indicators of reversal learning performance seem to be impaired by exposure to greater childhood unpredictability. For trial-by-trial learning performance, there were some main effects of childhood unpredictability, but they were inconsistent across experiments. Finally, for all outcomes and experiments, the current context did not moderate the effect of early childhood. I discuss possible explanations for these inconsistent findings and lay out new avenues for future research. Despite these inconsistent findings, this research remains important because it could help to identify the types of learning strategies that are most effective for success among people from disadvantaged backgrounds.

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Introduction

Stressful and adverse environments have a profound impact on children and their cognitive performance and development. The prevailing insight from research examining the effect of adverse environments on cognitive development is that negative experiences in childhood derails development, impairs the mind, and results in cognitive deficits. Despite this robust finding, this deficit-centered approach misses an important question: What cognitive abilities may be enhanced in people who are exposed to childhood adversity? This research question spurred the development of the "the specialization hypothesis", the notion that children should develop specialized cognitive abilities that are adapted to the stressful and adverse environments in which they grew up. Rooted in evolutionary-developmental theory, the notion of specialization shifts scientific inquiry toward what people from disadvantaged backgrounds may *do well* instead of exclusively on what they do poorly.

In the past few years, the concept of specialization has garnered initial support and stimulated new lines of research focused on discovering how adversity might shape instead of impair cognitive performance. For example, recent research has focused on testing whether and how early childhood adversity enhances specific aspects of attention and memory. To further expand this body of work, this dissertation examines whether and how learning abilities and strategies might also be enhanced by early childhood adversity. To do so, I first review contemporary models of cognition in the context of adversity. This includes the deficit model, the specialization hypothesis, and the sensitization hypothesis, which is an important corollary of the specialization hypothesis.

Then I consider the functional link between a specific form of adversity—environmental unpredictability—and learning outcomes. Using this framework, I then test how learning outcomes are affected by exposure to unpredictable environments earlier in life using well-established experimental procedures and different widely used learning paradigms.

Models of Cognition in Adverse Environments

The Deficit Model

The predominant view of the role of early adverse experiences in the development of cognitive abilities is captured best by the term *deficit.* The central premise of the deficit model is that early adverse experiences undermine normal cognitive development, which results in deficits in a variety of memory, learning, and executive functions (Farah et al., 2006; Shonkoff, 2012). Indeed, early-life adversity such as poverty, family conflict, deprivation, or trauma has been linked to myriad cognitive deficits (Frankenhuis & de Weerth, 2013), including poorer working memory performance (Bos, Fox, Zeanah, & Nelson, 2009; Farah et al., 2006; Hackman et al., 2014; Noble, McCandliss, & Farah, 2007), impaired executive functioning (Blair et al., 2011; Hostinar, Stellern, Schaefer, Carlson, & Gunnar, 2012; Hughes, Ensor, Wilson, & Graham, 2010; Noble, Norman, & Farah, 2005), lower intelligence and lower standardized test scores (Bradley & Corwyn, 2002), and worse language, reading, and math skills (Farah et al., 2006; Noble et al., 2005). Based on these findings, one prevailing view is that adverse childhoods typically impair cognition (Hackman, Farah, & Meaney, 2010; Karatsoreos & McEwen, 2013; McEwen, 1998, 2007).

Adverse environments usually do contain higher levels of chronic stress, which often have negative long-term effects on stress physiology along with the structure and function of brain regions that govern important cognitive abilities (Blair & Raver, 2012; Del Giudice, Ellis, & Shirtcliff, 2011; Karatsoreos & McEwen, 2013; McEwen, 2012). Thus, the focus of the deficit model has recently shifted from identifying impairments to tying such impairments to specific brain areas and systems that may explain them and also identifying subpopulations of individuals who either show increased vulnerability or resilience to adverse childhood experiences (Ellis, Bianchi, Griskevicius, & Frankenhuis, 2017). In general, however, the key conclusion of the deficit model remains the same: Growing up in a difficult, chaotic, and/or unpredictable environment typically impairs most forms of cognitive functioning.

An important limitation of the deficit model, however, is that it frames scientific inquiry in one direction. Because the deficit model implicitly assumes that early adversity is unilaterally responsible for cognitive impairments, it misses the opportunity to discover *whether* or *how* early adversity might have a more nuanced and perhaps adaptive pattern of effects on cognitive functioning. In addition, there is no logic embedded within the deficit model that connects major cognitive abilities to specific forms of adversity early in life. Instead, it lays out a framework from which only deficits are predicted to arise from adversity, whatever the type of adversity. Relatedly, the deficit model assumes that growing up in a safe, well-resourced, and predictable environment should lead to a fully functional, unimpaired suite of cognitive functions and abilities, which is not invariably true (REF).

Specialization Model

Although the overall negative effects of childhood adversity on cognitive functioning are indisputable, an evolutionary-developmental framework suggests that stressful childhood environments might not universally impair cognition, but instead may shape and direct it (Ellis et al., 2017; Frankenhuis & de Weerth, 2013). This distinction is important because, in contrast to the deficit model, the specialization model predicts that adverse childhood environments may have some specific positive, rather than universally negative, effects on certain types of cognitive functioning. Given that humans and other animals encountered stressful and unpredictable environments over the course of evolutionary history (Ellis, Figueredo, Brumbach, & Schlomer, 2009), organisms are likely to have certain cognitive adaptations for navigating these types of adverse environments (Ellis & Del Giudice, 2014; Mittal, Griskevicius, Simpson, Sung, & Young, 2015; Young, Griskevicius, Simpson, Waters, & Mittal, 2018).

Central to an evolutionary-developmental approach, therefore, is the notion of specialization (Ellis et al., 2017). Specialization is the idea that a person's mind becomes developmentally adapted ("specialized") for solving certain ecologically-relevant problems in the types of environments in which the person grew up. Thus, instead of being damaged by early stressful/adverse conditions, specialization suggests that certain cognitive abilities are shaped during early childhood in ways that might enhance reproductive fitness across a person's lifespan. Consistent with this reasoning, research using both animals and humans has found that adverse early-life environments tend to enhance specific cognitive functions (Ellis et al., 2017). For example, birds raised in non-threatening environments learn foraging strategies from their parents. However, birds reared in unpredictable environments also have the specialized ability to learn foraging strategies from both biologically-related and unrelated adults (Farine, Spencer, & Boogert, 2015). This more flexible learning style enables birds raised in unpredictable environments to respond to changing conditions better, such as when parents are not available to teach their offspring skills important for survival and eventual reproduction.

Similar types of specialization effects have been documented in rodents (Champagne, 2008; Oomen et al., 2010) and humans (Frankenhuis & de Weerth, 2013). For example, although traumatized and maltreated children show cognitive deficits in a number of domains, they exhibit heightened attentional vigilance and memory for threatening information (Goodman, Quas, & Ogle, 2010). Physically maltreated children also recognize angry faces more quickly than children who were not maltreated (Pollak, 2008; Pollak, Messner, Kistler, & Cohn, 2009). These findings are consistent with the notion that it may be particularly useful for people who were maltreated to identify and remember individuals who might pose a threat rapidly. Viewed together, these findings in both human and non-human animals suggest that early-life adversity does not invariably impair cognitive functioning; sometimes early-life stress may hone the mind in particular ways so individuals can more successfully navigate and deal with the challenges posed by certain types of adverse environments.

The Sensitization Model

An important extension of the specialization model is the idea that some cognitive abilities specialized by early-life circumstances may manifest only under particular conditions later in life (Ellis et al., 2017). This idea, known as *sensitization*, posits that supposed enhancements in cognitive functioning among individuals who grew up under specific adverse conditions should emerge, but only under conditions that resemble their early environments. In other words, early-life experiences should both specialize certain abilities *and* adaptively sensitize them in response to current environmental cues similar to those encountered earlier in life (Griskevicius et al., 2013; Griskevicius, Tybur, Delton, & Robertson, 2011; Mittal & Griskevicius, 2014).

Cast another way, the sensitization hypothesis predicts that specialized abilities shaped by adverse early-life conditions may not be detectable in benign, non-threatening circumstances. Instead, these abilities should be activated when people encounter similarly adverse conditions later in life. This idea has received some support in work with rodents. When tested under benign conditions, rats reared in harsh environments tend to perform worse on learning and memory tasks than rats reared in nurturing environments. However, when tested in threatening conditions—such as when a threat is experimentally induced in the laboratory (e.g., the presence of a predator)—rats reared in adverse environments show improved performance on these tasks (Bagot et al., 2009; Chaby et al., 2015).

Drawing on the notion of sensitization, recent studies with humans have also tested whether and how early childhood adversity enhances specific aspects of attention and memory. For example, Mittal, Griskevicius, Simpson, Sung, and Young (2015) investigated whether growing up in an unpredictable versus predictable childhood environment impacts the executive function of attention-shifting—being able to switch attention between goals or tasks quickly as reward patterns change. Mittal et al. (2015) predicted that growing up in an unpredictable environment should enhance attention-shifting because opportunities are fleeting in unpredictable environments and attention-shifting should be useful and perhaps adaptive when responding to constantly changing threats and opportunities. To test this hypothesis, they conducted a series of experiments that manipulated the current environmental context by having participants first view either a stressful news story about economic uncertainty or a control condition news story, after which participants completed a standard attention-shifting task. The findings were consistent with the sensitization hypothesis: Participants raised in more unpredictable childhood environments showed enhanced shifting performance in the stressful economic uncertainty condition, but not in the control condition. In other words, people who grew up in unpredictable early-life environments performed *better* at shifting, but only when the current environment was stressful due to uncertainty, similar to their childhoods.

In another set of studies, Young, Griskevicius, Simpson, Waters, and Mittal, (2018) investigated the sensitization hypothesis within the domain of working memory—the ability to store, access, and manipulate information over the short-term. Specifically, Young et al. (2018) examined how exposure to unpredictable childhood environments affects two central aspects of working memory: Memory updating and memory retrieval. Because working memory updating involves the ability to track the environment and quickly update memory with newly acquired information, Young and colleagues predicted that updating should be enhanced by exposure to unpredictable environments in childhood. In contrast, working memory retrieval—the ability to store information outside of conscious awareness and retrieve it later—should be less useful in unpredictable environments. Using the same basic experimental paradigm as Mittal et al. (2015), they found that exposure to more unpredictable childhood environments enhanced working memory updating abilities, but not working memory retrieval abilities. As anticipated by the sensitization hypothesis, however, this effect emerged only under conditions of current experimentally-induced uncertainty.

Learning and Unpredictability

Thus far, nearly all research examining specialization and sensitization has focused on how different forms of attention and memory are enhanced by childhood adversity. To extend this body of work, we now need to examine whether these attention and working memory effects are also witnessed in broader learning abilities and strategies. For example, is it the case that enhanced shifting and working memory updating abilities reflect more complicated, multi-faceted learning abilities?

One important hypothesis is that environmental unpredictability might also impact *reversal learning*, which is the ability to use feedback to learn reward contingencies that change over time either better or more quickly. Reversal learning is important because it indexes cognitive flexibility and the degree to which individuals are able to adapt their current behavior to feedback from the current environment (Izquierdo, Brigman, Radke, Rudebeck, & Holmes, 2017). In a typical reversal learning paradigm, participants must learn which of two stimuli (typically visual) tends to be rewarded more often. Because option is rewarded more often than the other, learning should be guided by this feedback. Once the initial association is formed, the previously unrewarded option becomes rewarded more often (i.e., the reward probabilities reverse). One important feature of reversal learning paradigms, therefore, is the capacity to use feedback histories to adjust behavior to changing stimulus-outcome contingencies in a flexible manner (Culbreth, Gold, Cools, & Barch, 2016; Izquierdo et al., 2017; Tsuchida, Doll, & Fellows, 2010).

Cognitive flexibility as indexed by reversal learning paradigms can be assessed in a number of different ways. Research has traditionally focused on both the number of correct responses across trials and the number of perseverative errors, or the tendency to continue choosing a previously rewarded response after a reversal has occurred (Izquierdo et al., 2017). These more global responses measure the extent to which participants change (adapt) their choices in response to recent feedback. However, it is also possible to measure trial-by-trial behavior to index the use of different learning strategies in reversal learning paradigms (den Ouden et al., 2013; Izquierdo et al., 2017; Tsuchida et al., 2010). For example, some individuals might learn reward contingencies by tracking all of the feedback from all of their past choices in order to make subsequent choices, using all of the information they have received (Izquierdo et al., 2017). Other individuals, however, might simply use the most recently received information to learn reward contingencies, ignoring their older choices and earlier reward patterns (den Ouden et al., 2013; Rudebeck & Murray, 2008).

Following this logic, one prediction is that exposure to more predictable environments early in life should lead individuals to integrate and use information from *all* of their feedback experiences in a reversal learning paradigm. The rationale for this prediction is that, for people who grew up in more predictable environments, information is more likely to remain stable over time and, as a consequence, using all available information across time is a better (i.e., more optimal) strategy (Dunlap & Stephens, 2009, 2012). In contrast, exposure to more unpredictable environments characterized by frequent and unexpected changes that may render old information less relevant in terms of forecasting what might happen in the future (Dunlap & Stephens, 2012). Thus, in unpredictable environments, it should be more functional to utilize a strategy that relies more on recent experiences and new information, largely ignoring the overall feedback history.

Within reversal learning paradigms, individuals exposed to predictable childhood environments should show better overall performance. This is because, when the environment is stable, it is more optimal to integrate all experience and feedback histories to inform learning about rewards and punishments in the environment. In contrast, within the same paradigm, individuals exposed to unpredictable childhood environments should be guided more by trial-by-trial feedback rather. For example, instead of tracking which stimulus choice has been rewarded the most on average across time, these individuals may be more inclined to base their choices on the most recent feedback they have received. Cast another way, because the information in rapidly fluctuating environments quickly becomes uninformative, individuals in these environments should attend to recent information to help them track current rewards and punishments. Accordingly, individuals exposed to more unpredictable environments should enact a “lose-shift” strategy (changing a response preference after receiving negative feedback) and a “win-stay” strategy (maintaining a response preference following positive feedback).

Critically, if recent feedback is more powerful in guiding learning among individuals exposed to more unpredictable environments, both lose-shift and win-stay learning strategies should be enacted. These strategies may be particularly relevant when the current context is also uncertain, as per the sensitization model. More specifically, lose-shift and win-stay learning strategies may become activated when the individuals exposed to more childhood unpredictability feel the current environment is uncertain but not when it is neutral or benign. This prediction follows for two reasons. First, recent research has found that cognitive adaptations to childhood unpredictability are not visible unless they are activated by current stressors (Mittal et al., 2015; Young et al., 2018). Second, cues of uncertainty might be particularly relevant for bringing these learning strategies online because they signal that an individual is currently in an environment that could change suddenly.

Current Research

To date, it remains unclear whether and how exposure to an early-life unpredictable environment is related to different learning strategies. To address this gap, I conducted four experiments using different variations of the same probabilistic learning paradigm. Experiment 1 explored the effect of exposure to childhood unpredictability on basic reinforcement learning to establish how individuals learn in a probabilistic learning task without any reward reversals. Experiments 2 and 3 used the same probabilistic learning task, but both experiments contained reward reversals. Experiment 2 did so after a learning criterion (i.e., a predefined number of correct responses in a row) was reached, whereas Experiment 3 introduced a reward reversal after a fixed number of trials. Finally, Experiment 4 explored how rapidly occurring reward reversals affected learning among individuals exposed to high versus low childhood unpredictability. All experiments also examined the extent to which the impact of exposure to an unpredictable childhood depended on currently uncertain conditions, which were experimentally manipulated.

Experiment 1: Basic Reinforcement Learning

Experiment 1 was designed to explore how exposure to unpredictability early in life might affect reinforcement learning in the context of a probabilistic learning paradigm without any reward reversals (e.g., a basic reinforcement learning paradigm). We measured learning by administering a probabilistic learning task where participants had to learn which of two images were more often rewarded by probabilistic, computer-delivered feedback; one option was associated with a reward on 70% of trials, and the other option was associated with a reward on the other 30% of trials. The goal of Experiment 1 was to establish the extent to which there might exist underlying differences in global learning outcomes, particularly overall learning as indexed by: (1) the proportion of correct responses and perseverative errors and/or (2) differences in trial-by-trial learning outcomes, such as lose-shift or win-stay behavioral choices.

Method

Participants. Two-hundred and ninety-eight undergraduates[1] (139 females, 157 males, 2 did not indicate their sex) were recruited from an introductory to marketing course to participate in the study exchange for course credit. The mean age of participants was 20.4 (*SD* = 1.92). The ethnic background of the sample was 17.4% Asian/Asian American, 3% Black/African American, 3.7% Hispanic/Latino, 71% White, 3% mixed descent, and 3% indicated other.

Procedure. Participants were told that two different phenomena were being studied in the session: Cognitive abilities, and how people process information. Participants first practiced and familiarized themselves with the learning task (see below). After the practice round, participants started the information processing part of the study, which was framed as a task that assesses how people process information from the news. All participants then watched a news slideshow, which was the experimental manipulation. Participants were then told that, later in the study, they would complete a writing task asking about the content of news slideshow. Directly following the news slideshow, participants were told they would work on the first cognitive task, which involved the first set of the probabilistic learning task (see below). Upon completing the first set, participants were asked to recall the news slideshow they viewed earlier and

[1] Sample sizes were determined by the number of eligible subjects able to participant in a semester with the target goal of achieving similar or larger samples sizes than previous studies in this area (e.g. Mittal et al., 2015; Young et al., 2018). Power analyses were not conducted because plausible effect sizes in the domain of reinforcement learning have not been estimated prior to this research. Furthermore, with respect to Experiments 2 and 3, there are no agreed upon analytical solutions to determine the power of mixed-effects models, nor are there readily available analytical solutions to determine the power of single coefficients in linear models.

describe its most important and vivid aspects. This task served as the manipulation "booster shot" to reinstate either an uncertain (experimental) or a control (neutral) current context (Mittal et al., 2015; Young et al., 2018). Participants then completed the second set of probabilistic learning trials. After the completion of the learning task, participants provided information about their childhood background and demographics.

Uncertain context manipulation. Participants were randomly assigned to either a control or an economic uncertainty condition. Both conditions involved viewing a news article slideshow ostensibly from the *New York Times*. The article was formatted to appear like a web-article featuring the newspaper's logo, font, and style. The slideshows were identical to the previous research (Young et al., 2018). Both the control and uncertainty slideshows contained five images accompanied by a one-sentence caption with each image. Each slide was displayed one at a time for 10 seconds. The content of the economic uncertainty slideshow featured a worsening and unpredictable economic climate. The control slideshow contained images and text describing issues of modern computer technology.

Probabilistic Learning Task. Participants were told that, during the task, they would see two images. Specifically, they were told the following:

"During this game, you will see two images that will appear in one of four locations on the screen. One image is correct more often than the other. You must choose the image that tends to be correct more often. At first, you will not know which image tends to be correct more often. During each trial, use the arrow keys on your keyboard to select an image. Then, the computer will tell you if your choice was correct or incorrect.

If your choice is correct, you will see a smiley face. If your choice is incorrect, you will see a frowny face."

Participants then proceeded to practice the learning task. After being exposed to experimental the manipulation (i.e., uncertainly vs. control slides), they completed 24 trials of the learning task with one set of images. Upon completing these 24 trials, participants completed another 24 trials with a new, completely unfamiliar pair of images. On each trial, one image was correct 70% of the time and the other was correct 30% of the time. After the manipulation booster (described below), participants completed two more sets of learning 24 trials (each set involved a new pair of unfamiliar images).

There were four outcome variables of interest. The first was simply the proportion of correct responses in each set. The second outcome was the number of perseveration errors made across the task. Perseveration errors were defined as any sequence of two or more errors. The third outcome was the frequency of lose-shift behavior. Lose-shift behavior was operationalized as the number of times participants changed their stimulus selection after receiving negative feedback. This value was then divided by the number of times each participant received negative feedback. The final outcome was the frequency of win-stay behavior. Win-stay behavior was defined as all instances where participants received positive feedback and subsequently chose the same stimulus on the next trial. This value was then divided by the total number of times each participant received positive feedback. All outcome measures were averaged across each set. In total, there were 4 sets of 24 trials (see Table 1 for descriptive statistics).

Manipulation booster. After completing the first round of the reversal learning task, participants completed a manipulation booster to reinstate an uncertain or a control state of mind (Mittal et al., 2015; Young et al., 2018). Participants were instructed to: "Please think back to the slideshow you viewed earlier and write about the most important and vivid aspects of the slideshow in detail."

Childhood unpredictability. Participants reported their level of exposure to unpredictability in their childhood environments. Participants were instructed to: "Think back to your life when you were younger than 10. This time includes preschool, kindergarten, and the first few years of elementary school." Participants then answered 8 items that assessed their level of exposure to unpredictability in childhood, which were used in previous research (Young et al., 2018). Each item was scored on a scale anchored at 1 - *not at all* to 7 - *extremely*. Items were then averaged to create a composite childhood unpredictability score (M = 1.77, SD = 1.09, α = .91).

Childhood Socioeconomic Status. Participants also reported information on their socioeconomic status (SES) during childhood. We used previously established items to measure childhood SES (Griskevicius et al., 2013, 2011; Mittal & Griskevicius, 2014; Mittal et al., 2015). The four items were: (a) "my family usually had enough money to buy things," (b) "I lived in a relatively wealthy neighborhood" and (c) "I attended a good school (or schools), (d) my family struggled financially, and (e) my parents or legal guardians had good jobs." These items were averaged to construct a childhood SES composite (M = 5.54, SD = 1.46, α = 0.87).

Results

The deficit model anticipates that exposure to more unpredictability early in life should have a negative association with overall reversal learning performance, particularly lower overall accuracy and more perseverative errors. On the other hand, the sensitized-specialization hypothesis anticipates that more unpredictability early in life might actually enhance trial-by-trial reversal learning outcomes such as either lose-shift and win-stay behavioral choices, especially under current uncertainty. That is, exposure to more unpredictability in childhood—especially under conditions of current uncertainty—should shift learning strategies toward the use of more recent information rather than leveraging all information from prior trials. This is because favoring more recent experiences should be most informative when a person's earlier environment fluctuated rapidly.

I used linear regression analysis to test this possibility. I ran 4 models, one for each outcome. Each model contained three variables: The 2 experimental conditions as an effects-coded categorical variable (control = -1, economic uncertainty = 1), childhood unpredictability as a continuous variable (standardized), and the interaction of the two variables. Note that for each analysis reported below, I also entered childhood SES as a grand-mean centered variable and the interaction between childhood SES and experimental condition into this analysis to compare the effect of childhood SES and childhood unpredictability directly. There were no interactions between SES and condition nor main effects of SES. As such, the results reported below are from the models that did not contain SES.

Proportion Correct. For the proportion of correct responses, there was no main effect of experimental condition (see Table 2), but there was a main effect childhood unpredictability. It indicated that higher levels of exposure to childhood unpredictability were associated with fewer correct responses in the reinforcement learning task overall. There was no interaction between experimental condition and childhood unpredictability.

Perseveration. For perseveration errors (the number of trials in which participants selected the incorrect stimulus two or more times divided by the total number of trials completed), there also was a main effect of experimental condition, indicating that participants made fewer perseveration errors in the uncertainty condition compared to the control condition (see Table 2). There was also a main effect of childhood unpredictability, indicating that individuals exposed to higher levels of childhood unpredictability made more perseverative errors (see Table 2). There was no interaction between experimental condition and childhood unpredictability (see Table 2).

Lose-Shift Behavior. For lose-shift behavior, there was no main effect of experimental condition, but there was a main effect of childhood unpredictability. It indicated that exposure to more unpredictability early in life was associated with more lose-shift behavior (see Table 2). However, there was no interaction between experimental condition and childhood unpredictability (see Table 2).

Win-Stay. For win-stay behavior, there was no main effect of experimental condition, but there was a main effect of childhood unpredictability, which indicated that higher levels of childhood unpredictability were associated with less win-stay behavior (see Table 2). There was no interaction between condition and exposure to childhood unpredictability (see Table 2).

Discussion

Experiment 1 examined how growing up in an unpredictable versus predictable environment impacted reinforcement learning outcomes under conditions of current uncertainty. The results revealed a consistent main effect of childhood unpredictability: People who grew up in a more unpredictable environment had lower overall accuracy, made more perseverative errors, engaged in more lose-shift behavior, and also displayed less win-stay behavior. These effects are consistent with the notion that adverse childhood experiences generally impair learning processes. However, individuals exposed to higher levels of childhood unpredictability also displayed more lose-shift behavior, suggesting that exposure to childhood unpredictability may "calibrate" individuals to be more sensitive to negative feedback, which in turn affects their behavioral choices. It is important to note that, despite this effect on lose-shift behavior, childhood unpredictability did not interact with experimental condition for any of the outcomes, indicating an overall lack of evidence consistent with sensitized-specialization hypothesis.

The learning paradigm used in Experiment 1 measured basic reinforcement learning. Thus, it remains possible that introducing a reward probability reversal, such as those used in many reversal learning tasks, may reveal different effects than those found in this first experiment. For example, it could be the case that learning strategy adaptations become more relevant when changes occur *within* the learning task context. Experiments 2 and 3 were designed to explore this possibility.

Experiment 2 – Reversal Learning with Fixed Reversal Criterion

Experiment 1 measured learning strategies using a basic reinforcement learning paradigm without any reward reversals. Experiment 2 used the same learning paradigm. However, after 24 trials of learning which stimulus image was rewarded more often, the reward probabilities reversed. Thus, one possibility is that, even though there was no evidence in support of the sensitized-specialization hypothesis in Experiment 1, introducing reward reversals may differentially impact individuals exposed to greater childhood unpredictability. In other words, individuals from more unpredictable childhood backgrounds may be better at coping with rapid environmental changes, such as shifting reward contingencies. As such, one prediction is that the same overall learning outcomes measured in Experiment 1 (e.g., the proportion of correct and perseverative errors) might depend on exposure to childhood unpredictability, experimental condition, and trial type (initial learning acquisition or reversal trials). In addition, it could be that trial-by-trial learning performance changes as a function of trial type, such that lose-shift and win-stay behavioral choices depend on exposure to childhood unpredictability, condition, and trial type. That is, differences in lose-shift and win-stay behavior may only be observed initially (in the acquisition phase of the task) or after a reversal has occurred.

Method

Participants. Three hundred and twenty-five undergraduates (146 females, 179 males) were recruited from an introductory to marketing course and received course credit for completing the study. The mean age of this sample was 20.1 (*SD* = 1.62). The ethnic background of the sample was 14.2% Asian/Asian American, 2.8% Black/African American, 1.5% Hispanic/Latino, 76.3% White, 4.3% mixed descent, and 1% indicated other.

Procedure. The procedure of Experiment 2 was nearly identical to Experiment 1. We used the same experimental manipulations in the control and the uncertainty conditions, the same study procedures, the same measure of childhood unpredictability (M = 1.76, SD = 1.05, α = .90), and childhood SES (M = 5.45, SD = 1.16, α = .87). That is, participants were first introduced to the tasks they would complete. They then were exposed to the experimental manipulation, followed by a probabilistic reversal learning task, a manipulation booster, and another set of reversal learning trials. After this, they answered questions regarding their childhood background. The only difference between Experiments 1 and 2, therefore, was the learning task. In Experiment 1, reward and punishment probabilities remained the same across each stimulus set. In Experiment 2, the reward probabilities were reversed halfway through each stimulus set (see below).

Probabilistic Reversal Learning Task. Participants were told that, during the task, they would see two images. Specifically, they were told the following:

"During this game, you will see two images that will appear in one of four locations on the screen. One image is correct more often than the other. You must choose the image that tends to be correct more often. At first, you will not know which image tends to be correct more often. During each trial, use the arrow keys on your keyboard to select an image. Then, the computer will tell you if your choice was correct or incorrect. If your

choice is correct, you will see a smiley face. If your choice is incorrect, you will see a frowny face. Note that the 'correct' image might change. If this happens, the other image will be correct most of the time. In general, try to stick with the image that tends to be correct more often. If you think the correct image has changed, choose the other image."

Participants then practiced the reversal learning task. After being exposed to the experimental manipulation, they completed 48 trials of the reversal learning task. On each trial, one image was correct 70% of the time and the other was correct 30% of the time. After the 24^{th} trial, these contingencies completely reversed. After the manipulation booster, participants then completed another 48 trials, with another complete reversal (again, after 24 trials) with two novel stimuli to choose.

The same outcome variables were aggregated for this task. These were the proportion of correct responses, number of perseveration errors, frequency of lose-shift behavioral choices, and frequency of win-stay choices. Each of these outcome variables was averaged across both sets and trial types, that is, regardless of whether the trial was during the initial acquisition phase (the first 24 trials) or the reversal phase (the second 24 trials). Thus, each participant received two scores per outcome: Scores during the acquisition phase and during the reversal phase of the task (see Table 3 for descriptive statistics).

Results

I used the same data analytic approach as Experiment 1 with one important difference. Instead of using standard linear regression, I used a mixed-modeling approach in order to model the within-person effect of trial type (i.e., initial acquisition or reversal).

I ran four mixed-models (one for each outcome) and tested for the fixed-effect of a possible three-way interaction between experimental condition (between-subjects), childhood unpredictability (between-subjects), and trial type (within-subjects). All lower-order fixed effects were also entered into the model (the main effects and two-way interactions) as well as a random intercept, which accounted for the fact that reversal learning scores were nested within subjects (i.e., there was a global score for initial acquisition trials and another score for reversal trials per outcomes for each participant). Again, there no effects of childhood SES or interactions between childhood SES. Thus, the analyses reported below do not contain these terms.

Proportion Correct. For the proportion of correct responses, there was no main effect of experimental condition or childhood unpredictability (see Table 4). There was a main effect of trial type, indicating that accuracy was significantly lower during the reversal round compared to the initial acquisition phase (see Table 4), which is typical of reversal learning tasks. However, there was no interaction between the experimental condition and childhood unpredictability, between experimental condition and trial type, or between childhood unpredictability and trial type. There was also no three-way interaction between childhood unpredictability, condition, and trial type.

Perseveration. For perseveration errors, there was again no main effect of experimental condition and no main effect of childhood unpredictability (see Table 4). There was a main effect of trial type, indicating that perseveration errors were significantly more frequent during the reversal phase of the reversal learning task compared with the acquisition phase (see Table 4). Importantly, however, there were no higher-order two-way interactions between childhood unpredictability and experimental condition, condition and trial type, or unpredictability and trial type (see Table 4). Finally, there was no three-way interaction between childhood unpredictability, condition, and trial type.

Lose-Shift Behavior. For lose-shift behavior, there was again no main effect of experimental condition or childhood unpredictability (see Table 4). There was a main effect of trial type, indicating that lose-shift behavior was less frequent during the reversal phase of the task compared to the acquisition phase (see Table 4). There were no two-way interactions, but there was a marginal three-way interaction between childhood unpredictability, condition, and trial type. Figure 2 depicts this marginal interaction. In the control condition, both individuals exposed to higher and lower levels of childhood unpredictability show the same decrease in lose-shift behavior from the acquisition phase to the reversal phase of the task. In the uncertainty condition, however, individuals exposed to higher childhood unpredictability exhibited higher levels of lose-shift behavior compared to individuals exposed to lower levels of childhood unpredictability (see Figure 2). However, this was apparent only during the acquisition phase of the task; during the reversal phase, there was little difference in lose-shift behavior among individuals exposed to higher versus lower levels of childhood unpredictability (see Figure 2).

Win-Stay. For win-stay behavior, there was no main effect of experimental condition and no main effect of childhood unpredictability (see Table 4). There was a main effect of trial type, indicating that win-stay behavior was lower in the reversal phase of the task compared to the acquisition phase (see Table 4). Importantly, there were no two-way interactions or a three-way interaction between condition, childhood unpredictability, and trial type (see Table 4).

Discussion

Experiment 2 was designed to explore how growing up in an unpredictable versus predictable environment influences reversal learning outcomes under conditions of differential uncertainty. Unlike Experiment 1, participants in Experiment 2 experienced a complete reversal in the reward structure of the learning task. In order to be successful, they first had to learn which image was rewarded more often and then break this association when the reversal occurred, learning to select the previously non-rewarded image. As expected, all four learning outcomes differed between the acquisition and the reversal trials. Specifically, overall accuracy and perseverative errors were higher during reversal trials compared to acquisition trials, and lose-shift and win-stay behavioral choices decreased, although this difference was less pronounced than it was for accuracy and perseveration errors.

Critically, there were no main effects of or interactions between childhood unpredictability and the experimental condition, indicating that exposure to more unpredictability early-life environments was not associated with any of the four learning outcomes, nor did the effect of unpredictability depend on current environmental uncertainty. In addition, neither childhood unpredictability nor experimental condition interacted with trial type, suggesting that these variables were not differentially associated with performance during the acquisition and reversal phases of the task.

However, there was a marginal three-way interaction between childhood unpredictability, condition, and trial-type for lose-shift behavior. Figure 2 shows that during the acquisition phase and under conditions of uncertainty, individuals exposed to more childhood unpredictability engaged in more lose-shift behavior. This is at least partially consistent with Experiment 1 in which individuals exposed to high levels of childhood unpredictability also showed more lose shift behavior, especially since the learning task in Experiment 1 did not introduce reward reversals. More specifically, both Experiments 1 and 2 showed similar lose-shift effects during the intial learning of an association. However, there was no interaction between the experimental condition and childhood unpredictability in Experiment 1.

In summary, there is little evidence from Experiments 1 or 2 that reversal learning performance is specialized by childhood unpredictability or is sensitized by experimentally-induced current uncertainty. The only outcome that showed at least partial consistency with respect to these predictions across Experiments 1 and 2 was lose-shift behavior. One reason for this finding might be that lose-shift behavior depends on some degree of punishment sensitivity or responsivity. As such, one possibility is that unpredictable childhood environments increase sensitivity and vigilance toward threats and punishments and such heighted sensitivity may translate in to more frequent lose-shift behavior.

Experiment 3 – Reversal Learning with Learning Criterion

One possible reason for the lack of effects in Experiments 1 and 2 is that the reward probabilities of both the reinforcement learning task in Experiment 1 and the reversal learning task in Experiment 2 were too difficult. That is, 70%/30% reward probabilities may have made learning too difficult to detect differences in learning strategies as a function of exposure to childhood unpredictability and/or conditions of current uncertainty. Thus, Experiment 3 was designed to adjust the reward probabilities to 80%/20% to make the feedback easier to infer and process during the reversal learning task used in Experiment 2. In addition, instead of reversing the reward probabilities halfway through the task, the reversal learning task in Experiment 3 was programmed to reverse reward probabilities after only 8 consecutive correct responses. This was done to ensure that the probabilities reversed only after it was clear that learning had occurred first. Thus, Experiment 3 was designed to test the same predictions examined in Experiment 2, but with a different reversal learning task structure.

Method

Participants. Three hundred and forty-eight undergraduates (159 females, 189 males) were recruited from the same introductory to marketing course and granted course credit for their participation. The mean age of this sample was 20.4 (*SD* = 1.80). The ethnic background of the sample was 10.6% Asian/Asian American, 2.3% Black/African American, 2.6% Hispanic/Latino, 78.4% White, 3.1% mixed descent, and 3% indicated other.

Procedure. The procedure of Experiment 3 was similar to Experiment 2; we used the same experimental manipulations, study procedures, measure of childhood unpredictability ($M = 2.01$ $SD = 1.25$, $\alpha = .92$), and childhood SES ($M = 4.37$, $SD = .46$, $\alpha = .89$). However, the reversal learning tasked differed in the following way: The task introduced reward reversals based on a learning criterion (see below) instead of automatically reversing reward probabilities halfway through each set of trials.

Probabilistic Reversal Learning Task. In the reversal learning task of Experiment 3, participants were told they had to determine which of two distinct stimuli is more rewarding by using feedback provided by the computer. On each trial, one image was rewarded 80% of the time. After participants selected the correct image eight times in a row, the reward contingencies reversed. In other words, reward probabilities reversed only when participants demonstrated that they had learned which image was correct initially by selecting the correct image eight times in a row. If participants failed to select the correct image eight times in a row, the set ended after a maximum of 50 trials. This process occurred 3 times for each set; participants completed an initial acquisition phase, a reversal phase (contingent on performance in the acquisition phase), and then one more reversal (contingent on performance in the previous phase). Directly following the reversal learning task, participants completed the manipulation booster and subsequently completed another set of the reversal learning task with two new stimuli, which followed the same structure as the first set.

The same outcome variables were calculated and aggregated from this task in Experiment 3. These were the proportion of correct responses, number of perseveration errors, frequency of lose-shift behavioral choices, and frequency of win-stay choices. Each of these outcome variables was averaged across sets and trial types, that is, regardless of whether the trial was during the initial acquisition phase (the first 24 trials) or during the reversal phase (the second 24 trials). Each participant, therefore, received two scores per outcome: one during the acquisition phase and one during the reversal phase of the task (see Table 5 for descriptive statistics).

Results

The same data analytical approach used in Experiment 2 was also used in Experiment 3. However, to model quadratic effects of trial type, I also tested for both the linear and quadratic effects of trial type. Specifically, I used a mixed-modeling approach to model the linear and quadratic within-person effects of trail type (initial acquisition, reversal 1, and reversal 2. I once again ran four mixed-models (one for each outcome) and tested for the fixed effects of a linear and a quadratic three-way interaction between experimental condition (between-subjects), childhood unpredictability (between-subjects), and trial type (within-subjects; squared for the quadratic interaction). All lower-order fixed effects were also entered into the model (the main effects and two-way interactions), as well as a random intercept for each participant. Like all previous studies, there were no consistent effects of childhood SES or interactions between SES and condition or trial-type, thus all models below do not include childhood SES.

Proportion Correct. For the proportion of correct responses, there was a main effect of experimental condition, indicating that overall accuracy was lower in the uncertainty condition compared to the control condition (see Table 6). In addition, there was a main effect of childhood unpredictability, showing that individuals who were exposed to higher levels of childhood unpredictability tended score lower in overall accuracy (see Table 6). There was a main effect of trial type, indicating a linear decrease in accuracy across the three phases of the task. However, there was also a quadratic effect of trial type (see Table 6 and Figure 3); for all participants, overall accuracy tended to decrease after the first reversal and then increase after the second reversal. There were no interactions between experimental condition and childhood unpredictability, between experimental condition and trial type (linear or quadratic), or between childhood unpredictability and trial type (linear or quadratic; see Table 6). There was also no three-way interaction between childhood unpredictability, condition, and trial type (linear or quadratic; see Table 6).

Perseveration. For perseveration errors, there was a marginal main effect of condition, with marginally higher perseverative errors in the experimental condition compared to the control condition. There was also a main effect of childhood unpredictability, indicating that higher exposure to childhood unpredictability was associated with more perseverative errors (see Table 6). Once again, there was a main effect of trial type, indicating that perseveration errors were significantly more frequent across the three phases of the reversal learning task. Moreover, there also was a quadratic effect of trial type. It revealed that after an initial increase in perseverative errors following the first reversal, there was a subsequent decrease after the second reversal (see Table 6). Importantly, however, there were no higher-order two-way interactions, except for a marginal interaction between childhood unpredictability and the quadratic trial type term, suggesting that the number of perseverative errors marginally increased more for individuals exposed to higher childhood unpredictability compared to those exposed to lower childhood unpredictability (see Table 6 and Figure 3). Finally, there was no three-way interaction between childhood unpredictability, condition, and trial type (linear or quadratic).

Lose-Shift Behavior. For lose-shift behavior, there again were no main effects of condition, childhood unpredictability, or the linear trial type term (see Table 6). However, there was a main effect of the quadratic trial type term, indicating that lose-shift behavior tended to drop during the first reversal phase, but then increased after the second reversal phase (see Table 6 and Figure 3). There were no two-way interactions except for an interaction between childhood unpredictability and the quadratic trial type term (see Table 6). As shown in Figure 3, for individuals exposed to higher childhood unpredictability, lose-shift behavior tended to show a decrease followed by a subsequent increase across the learning phases of the task. However, individuals exposed to lower childhood unpredictability tended to display relatively similar levels of lose-shift behavior across the entire task. Finally, there were no three-way interactions (see Table 6).

Win-Stay. For win-stay behavior, there was a main effect of experimental condition, suggesting that win-stay behavior decreased across the learning phases of the task. There was a marginal main effect of childhood unpredictability, suggesting that win-stay behavior was marginally less frequent among individuals exposed to higher levels of unpredictability than those exposed to lower childhood unpredictability (see Table 6). There was no main effect of the linear trial type term, but there was a main effect of the quadratic term, indicating that win-stay behavior tended to drop and then increase slightly across the learning phases of the task (see Table 6). Importantly, there were no two-way interactions or a three-way interaction between condition, childhood unpredictability, and trial type (linear or quadratic, see Table 6).

Discussion

The results of Experiment 3 paralleled Experiment 2. Both experiments used a reversal learning task to examine the effect of exposure to unpredictability in early life. Critically, however, Experiment 3's learning criterion (8 correct choices in a row) dictated when reward reversals occurred during the reversal learning task. In addition, up to three trials sets were possible that had two reward reversals. Similar to Experiment 2, there were consistent effects of trial type (initial acquisition, reversal 1, and reversal 2) and particularly regarding the quadratic effect of trial type. Specifically, overall accuracy tended to decrease after the first reversal occurred and subsequently increased after the second reversal, whereas perseverative errors increased and then decreased. Furthermore, the main effect of childhood unpredictability for both outcomes revealed that this pattern was more pronounced for individuals exposed to higher levels of childhood unpredictability; that is, they had lower overall accuracy and made more perseverative errors. In addition, the lack of interactions involving childhood unpredictability and condition suggest no evidence for specialization-sensitization effects.

The pattern for win-stay and lose-shift behavior was less clear. For lose-shift behavior, there was a significant interaction between childhood unpredictability and the quadratic trial type term, such that greater lose-shift behavior depended both on exposure to early-life unpredictability and trial type. Specifically, across both the control and uncertainty experimental conditions, individuals expose to higher levels of childhood unpredictability tended to show less lose-shift behavior after the first reversal, but a subsequent increase in lose-shift behavior after the second reversal. On the other hand, individuals exposed to lower levels of childhood unpredictability tended to exhibit roughly the same level of lose-shift behavior across each trial type. For win-stay behavior, there was also a main effect of experimental condition. Specifically, in the control condition, individuals exposed to either higher or lower levels of childhood unpredictability showed consistently more win-stay behavior across each trial type. In the uncertainty condition, individuals exposed to higher childhood unpredictability showed less win-stay behavior across all trials compared to those exposed to lower unpredictability, although there was no interaction between experimental condition and childhood unpredictability. Furthermore, there were no other interactions.

These findings once again provide little support for any kind of specialization or sensitization effect in the context of reversal learning. While this is consistent with the general findings of Experiment 2, the findings of Experiment 3 actually reveal evidence of deficits in reversal learning performance, indicated by lower accuracy and more perseverative errors, as a function of exposure to greater childhood unpredictability. In summary and viewed together, Experiments 1, 2, and 3 show little evidence of enhanced reversal learning, both in terms of overall performance and trial-by-trial performance (e.g., lose-shift and win-stay behaviors).

Experiment 4 – Reversal Learning with Rapid Reversals

Thus far, there is little evidence that childhood unpredictability enhances reversal learning outcomes as well as little evidence that the effect of childhood unpredictability interacts with current exposure to uncertainty induced by experimental manipulations. Indeed, Experiments 1 through 3 suggest that reversal learning is generally impaired by exposure to greater childhood unpredictability. In terms of trial-by-trial learning style, the current research also suggests that individuals exposed to higher levels of childhood unpredictability typically show decreased win-stay behavior and increased lose-shift behavior, although this effect varies as a function of trial type and does not depend on current levels of uncertainty.

Importantly, both Experiments 2 and 3 implemented reward reversals either once or twice per learning set, respectively. Thus, a final parameter that may affect learning outcomes is the rate at which rewards are reversed. For example, it could be the case that, even when environments change, they change in somewhat predictable ways. In the reversal learning paradigms used thus far, participants had to adjust to relatively few changes that occurred at rather slow rates. Experiment 4, therefore, was designed to expose participants to many reward reversals throughout the task. If individuals exposed to higher levels of early-life unpredictability are adjusted to environments that change very frequently and unexpectedly, their learning outcomes may either be less adversely impacted by frequently reward reversals or perhaps even enhanced.

Method

Participants. Two hundred and sixty-nine undergraduates (132 females, 136 males, 1 person preferred not to say) were recruited from an introductory to marketing course and received course credit. The mean age of this sample was 20 (*SD* = 1.29). The ethnic background of the sample was 13% Asian/Asian American, 2.2% Black/African

American, 2.6% Hispanic/Latino, 77% White, 3% mixed descent, and 2% indicated other.

Procedure. The procedure of Experiment 4 was the same as all previous experiments. We used the same manipulations, general procedure, measure of childhood unpredictability (M = 1.92, SD = 1.16, α = .91), and childhood SES (M = 5.53, SD = 1.15, α = .88). The only difference was the structure of the reversal learning task. Like Experiments 2 and 3, Experiment 4 used a probabilistic reversal learning task; however, instead of introducing only 1 or 2 reward reversals, Experiment 4 introduced reversals every six trials. Because of this, the correct (rewarded) image changed eight times through the course of each reversal learning set, simulating a rapidly changing environmental setting.

Probabilistic Reversal Learning Task. In this reversal learning task, participants were again told they had to determine which of two distinct stimuli is correct (rewarded) most of the time. On each trial, one image was rewarded 80% of the time. However, the reward contingencies reversed after 6 trials, regardless of a participant's correct or incorrect responding. This meant that reward probabilities reversed eight times across 48 trials per set. Directly following the first set of the rapid reversal learning trials, participants completed the manipulation booster and then completed another set of the rapid reversal learning task with two new stimuli, which followed the same format as the previous set.

The same four outcome variables were computed from the task: proportion of correct responses, number of perseveration errors, frequency of lose-shift behavior, and frequency of win-stay behavior. These variables were aggregated across sets and trial types, with each participant having eight scores for each variable reflecting their performance across each reward probability sequence (see Table 7 for descriptive statistics).

Results

I used the same data analytical approach as in Experiment 3, with one important difference: Because there was no reason to believe that any reversal learning outcomes should differ as a function of trial type (initial acquisition and reversals 1 through 7), I modeled the main effects of both the linear and quadratic effects of trial type (a within-subjects variable), but did not test their interaction with either condition or unpredictability (between-subject variables). I used a mixed-modeling approach to model the linear and quadratic within-person effects of trail type and calculated a random intercept for all participants. I also ran a mixed-model for each reversal learning outcome and tested for the fixed effects of experimental condition (between-subjects), childhood unpredictability (between-subjects), and trial type (within-subjects; squared for the quadratic interaction). I also entered the interaction between experimental condition and exposure to childhood unpredictability. Finally, there were again no main effects of SES or interactions between SES and condition. As such, all results below are from models without SES included.

Proportion Correct. For the proportion of correct responses, there was no main effect of experimental condition or childhood unpredictability and no interaction between childhood unpredictability and condition (see Table 8). However, there was a main effect of the linear trial type term, suggesting that overall accuracy decreased in a linear fashion across the rapid reversal task. In addition, there was an effect of the quadratic trial type term, showing that overall accuracy tended to drop but then slowly increase toward the end of the task (see Figure 4).

Perseveration. For perseveration errors, there was again no main effect of condition or childhood unpredictability and no interaction involving these two variables (see Table 6). Again, however, there was a main effect of trial type, indicating that perseveration errors increased across the task after each reversal (see Table 6). Finally, there was also a quadratic effect of trial type, indicating an increase in perseverative errors during the first half of the task and a subsequent drop toward the end of the task (see Figure 4).

Lose-Shift Behavior. For lose-shift behavior, there was again neither a main effect of condition or childhood unpredictability nor an interaction between them (see Table 6). There was a marginal effect of both the linear trial type term and the quadratic trial type term. These marginal effects suggest that lose-shift behavior tended to increase over the course of the task and showed the sharpest increase during the last few trial type sets (see Figure 4).

Win-Stay. For win-stay behavior, there was no main effect of condition and a marginal main effect of childhood unpredictability, suggesting that win-stay behavior was lower among individuals exposed to higher compared to lower levels of childhood unpredictability (see Table 6). However, there was no interaction between condition and childhood unpredictability. Importantly, there was once again a main effect of both the linear and quadratic trial type terms, indicating that win-stay behavior decreased over the course of the task, but then increased slightly toward the end of the task.

Discussion

Experiment 4 found little difference in both global accuracy and perseverative errors among individuals exposed to higher versus lower childhood unpredictability. In addition, trial-by-trial lose-shift behavior did not differ as a function of exposure to childhood unpredictability, which is generally consistent with the findings from Experiments 2 and 3. Thus, despite the potentially more ecologically-relevant introduction of a rapidly changing task environment, Experiment 4 did not uncover any specialization or sensitization effects.

General Discussion

Recent studies have challenged the predominant view that adverse childhood experiences invariably impair the mind. Human studies investigating different aspects of attention and working memory, for example, have found initial evidence that the mind may become “specialized” by adverse experiences, with certain mental abilities allowing people to cope more effectively being shaped by specific environmental parameters. The current research investigated specialization in the context of cognitive flexibility and learning outcomes. Across 4 exploratory experiments, I tested how exposure to childhood unpredictability impacts both overall reversal learning performance and trial-by-trial learning styles. I also tested whether current, experimentally manipulated cues of economic uncertainty modulated reversal learning outcomes in relation to different levels of exposure to childhood unpredictability, based on the sensitization hypothesis and previous human studies (Ellis et al., 2017; Mittal et al., 2015; Young et al., 2018).

Regarding overall performance on the reversal learning tasks (indexed by overall accuracy and the number of perseveration errors), the findings suggest two general conclusions: 1) on average, reversal learning seems to be impaired by exposure to greater childhood unpredictability (e.g., there were no specialization effects, although Experiments 2 and 4 did reveal null effects of childhood unpredictability); and 2) there were no interactions effects involving childhood unpredictability and experimental condition in any of the experiments.

For trial-by-trial performance, Experiment 1 found main effects for childhood unpredictability, such that individuals exposed to higher levels of childhood unpredictability exhibited more lose-shift behavior, but less win-stay behavior. Experiments 2 and 3 found marginal effects of childhood unpredictability and reversal learning trial type, indicating that lose-shift behavior was heightened during the initial phase of the task for these individuals, but it did not differ relative to individuals from more predictable childhood environments during the later phases of the task. In addition, there were no effects of childhood unpredictability on win-stay behavior in Experiment 2. Experiments 3 and 4 revealed a marginal effect on win-stay behavior, suggesting that higher levels of exposure to childhood unpredictability were associated with less win-stay behavior. Furthermore, similar to the overall performance measures, lose-shift and win-stay behaviors were not predicted by the interaction between early childhood unpredictability and the experimental manipulation.

In contrast to previous studies of attention and memory (Mittal et al., 2015; Young et al., 2018), the current findings are inconsistent with the notion that learning outcomes—at least those assessed by reversal learning paradigms—are specialized and/or sensitized by childhood unpredictability and current cues of uncertainty. There are at least three possible explanations for the lack of these effects. First, it may be that reversal learning is generally impaired by adverse experiences, as predicted by the standard deficit model. More specifically, exposure to childhood unpredictability may simply impair one's ability to learn from punishments and rewards, which is consistent with research linking early life stress and impaired reward processing (e.g., Novick et al., 2018). Such impairments could arise because individuals may learn that rewards and punishments just randomly occur in unpredictable environments (Hanson et al., 2017; Novick et al., 2018).

A second possibility is that the reversal learning paradigm used in the current research was not ideal for discerning differences between individuals with different developmental exposures to unpredictability. For example, the abstract stimuli used in the tasks may have seemed irrelevant or may have been insufficiently motivating for participants to learn. Similarly, the rewards and punishments delivered during the tasks may have been of too little consequence or importance (smiley or frowny faces) to facilitate actual learning. A third possibility is that, even though childhood unpredictability seemed theoretically relevant for shaping reinforcement learning strategies, other forms of adversity exposure exert a stronger impact on reinforcement learning patterns. For example, because reinforcement learning involves learning based on punishments and rewards, it could be that exposure to harsh conditions—but not unpredictable conditions—shape learning strategies. If this is true, exposure to consistently harsh conditions, such as high levels of violence or fighting, might calibrate individuals to be especially attuned to punishment, thereby improving learning.

Finally, because the current findings do not address the role of genetics, the reinforcement learning effects (and lack thereof) reported in this current research might be attributable to inherited genetic predispositions and not childhood environments. Critically, previous research has found sizeable heritability estimates for many cognitive abilities and executive functioning (e.g., Friedman et al., 2008; Miyake & Friedman, 2012). Thus, there may be important genetic effects that went unmeasured and were not modeled in the current research.

Limitations

The current research has several important limitations. First, the reinforcement learning tasks used to measure learning outcomes were much shorter than typical learning tasks. For example, the reversal learning task used in Experiment 2 was modified to be much shorter (24 trials per learning phase) than other reversal learning studies, some of which have used 40 - 60 trials per learning phase (den Ouden et al., 2013; Tsuchida et al., 2010). In the current research, shortening the length of these tasks was crucial given the experimental manipulations. In order to maximize the effect of the experimental manipulations, the learning tasks needed to be shorter, and a manipulation booster was also added between sets of trials to ensure that feelings of uncertainty were maintained throughout the task, as has been done in previous studies (Griskevicius et al., 2013;

Mittal & Griskevicius, 2014; Mittal et al., 2015; Young et al., 2018). Nonetheless, this design change may have unintentionally reduced the reliability or perhaps the validity of the learning task. Furthermore, in all experiments, the response options were binary, which can introduce guessing behavior (rather than learning behavior) and may also have decreased the reliability or validity of the experiments. Future studies need to weigh the importance of task length and response option complexity (e.g., including more than two response options) against the importance of sustaining the effects of between-subject experimental manipulations.

Beyond issues with the learning measure's reliability or validity, the current research did not measure what is known as explore versus exploit behavior (Humphreys et al., 2015). For example, it could have been that the value representations of particular choices and their associated rewards were correctly updated in individuals exposed to varying levels of childhood unpredictability, but these individuals differed in the degree to which they explored versus exploited the rewards in each task. More specifically, individuals could choose to exploit the rewards in a particular learned association and, despite correctly learning this association, then explore the other response option to learn about its probability structure. Indeed, Humphreys et al. (2015) found that post-institutionalized children tend to exhibit more exploitative relative to exploratory behavior compared to children who were not institutionalized. In the current research, if individuals from more unpredictable backgrounds tended to exploit rewards more often explore both options, this could explain why they also were more inclined to make more perseverative errors after a reward reversal. Importantly, the learning tasks in the current research were not designed to measure explore versus exploit behavior. Future research should consider its role when measuring learning outcomes.

Another limitation of the current research was its lack of ecological validity. The many null effects obtained across each experiment could be due to the fact that the learning tasks employed were not sufficiently motivating or relevant to the participants. For example, the rewards and punishments used as feedback in all experiments were simple smiley and frowny faces, which may not have been meaningful or rewarding/punishing to participants. Although these stimuli are typically used in this type of research (e.g., Cools, Clark, Owen, & Robbins, 2002; Culbreth et al., 2016; den Ouden et al., 2013), other studies have used money (Fellows & Farah, 2003; Tsuchida et al., 2010), which may be more ecologically relevant and/or motivating to participants. In addition, the stimuli used in reinforcement learning tasks are usually intended to be neutral or abstract to reduce any previously associated rewards or punishments, but such abstract stimuli may be difficult to comprehend and/or irrelevant to participants.

In addition to the above issues with reinforcement learning, the measurement of childhood environment was retrospective. Although previous research has found that childhood unpredictability has consistent effects on cognition when it is measured either retrospectively or prospectively (e.g., Mittal et al., 2015), memory is highly fallible (e.g., Rubin, Rahhal, & Poon, 1998) and memory recall can be impacted by situational factors (e.g., Reuben et al., 2016). Prospective longitudinal studies (ideally with a genetically informed design) are necessary to overcome the limitations of retrospective measures.

Future Directions

Despite the lack of evidence for specialization and sensitization effects and mixed support for deficits, several possible avenues could be pursued to better understand the link between exposure to unpredictability and learning outcomes. One important future direction is to integrate neurocomputational theory and models into the measurement of learning outcomes. Within the neurocognitive literature, nuanced mathematical models have been developed to aid in the theorizing and measurement latent cognitive variables. Such models can be applied to reduce raw task data, such as all of the choices that are typically made during a reversal learning tasks, in order to more accurately estimate values approximating the cognitive variables of interest. For example, den Ouden et al. (2013) studied reversal learning outcomes in two ways. First, they analyzed raw reversal learning outcomes such as preservation, lose-shift, and win-stay behavior. However, they also used two neurocomputational models to analyze their data: The experienced-weighted attraction model (Camerer & Ho, 1999), and a reward and punishment learning reinforcement model (Frank, Moustafa, Haughey, Curran, & Hutchison, 2007). When applied to reversal learning data, the experienced-weighted attraction model estimates an experience decay parameter that quantifies the extent to which past experiences have a greater or lesser impact on choices. The reward and punishment reinforcement learning model separately estimates the extent to which rewards and punishments impact learning by computing a reward learning rate as well as a punishment learning rate. The general point is that bridging theory and models from computational neurocognitive research with evolutionary-developmental theory may be a fruitful avenue for future research.

In addition to incorporating more sophisticated models to measure theoretically relevant cognitive variables, it will also be critical to investigate learning outcomes using other learning tasks and paradigms. For example, learning tasks capable of isolating reward learning and punishment learning could help to identify whether both types of learning are impaired or whether one or the other remains intact (or perhaps even enhanced). For example, it could be that while reward learning is impaired or diminished among people exposed to greater early life adversity, punishment learning may remain intact or even enhanced. In addition, other forms of learning might be important to investigate. For example, simple associative learning or implicit learning are both outcomes that have not been tested within the specialization or sensitization frameworks. Finally, it will be important to investigate the stimulus space of learning tasks. Most learning tasks use abstract stimuli that participants presumably have never seen before. This is done intentionally to isolate the cognitive processes involved in learning and avoid the influence of previously acquired knowledge and associations from personal experience; however, it is possible that such abstract stimuli are not meaningful or are irrelevant to some participants. Thus, future research should investigate how learning operates when the stimuli are more ecologically relevant to participants and how this may impact their learning outcomes. However, regardless of the specific learning construct or stimuli used, careful thought and attention will be required to derive nuanced predictions about how exposure to particular dimensions of the environment might impair or enhance different learning strategies and outcomes.

Conclusion

Across four experiments, this dissertation tested how reinforcement learning abilities may be impacted and potentially enhanced by exposure to unpredictable environments in childhood. Little evidence was found for this hypothesis, both in terms of general learning abilities or more nuanced trial-by-trial learning behaviors. These findings suggest that, on the whole, exposure to greater unpredictability is not associated with reinforcement learning outcomes and may actually impair them, consistent with the deficit model (Hackman et al., 2010). Despite the lack of evidence for enhancements, however, it remains possible that other forms of learning could be enhanced by early life adversity. As such, future research should investigate whether and how different types of adverse experiences affect important learning constructs and outcomes, which could elucidate how people who have experienced specific forms of adversity interpret feedback and how they leverage it to optimize learning in relation to their past and/or current environments. More importantly, uncovering and understanding potential enhancements in learning abilities and strategies could provide crucial insights for future intervention in educational settings. For instance, it could lead to tailored pedagogical techniques designed to improve learning for people from different backgrounds, such as redesigning classroom environments and materials that work with the unique strengths of each student (Ellis et al., 2017). More broadly, this research could help identify and leverage the unique abilities of people from disadvantaged backgrounds to reduce inequality and help to close the achievement gap.

Table 1. Correlations and descriptive statistics for all variables in Experiment 1.

Variable	**1**	**2**	**3**	**4**	**5**	**6**
Correlations						
1. Correct	-					
2. Perseveration	-0.88**	-				
3. Lose-Shift	-0.59**	0.26**	-			
4. Win-Stay	0.77**	-0.47**	-0.54**	-		
5. Child Unpredictability	-0.16**	0.13*	0.12*	-0.12*	-	
6. Child SES	0.05	-0.06	-0.06	-0.02	-0.38**	-
Descriptive Statistics						
N	298	298	298	298	298	298
Mean	0.68	0.15	0.45	0.76	1.77	5.45
SD	0.15	0.1	0.18	0.18	1.09	1.15
Min	0.21	0	0	0.19	1	1
Max	1	0.67	0.9	1	6.25	7

Note: * $p < .05$, ** $p < .01$, *** $p < .001$

Table 2. Regression results for Experiment 1.

Model	**Term**	**β**	**95% CI**
Correct			
	Condition	0.07	[-0.04, 0.19]
	Unpredictability	-0.16**	[-0.28, -0.05]
	Condition × Unpredictability	0.05	[-0.06, 0.17]
Perseveration			
	Condition	-0.12*	[-0.23, -0.01]
	Unpredictability	0.14*	[0.02, 0.25]
	Condition × Unpredictability	-0.05	[-0.17, 0.06]
Lose-Shift			
	Condition	0.03	[-0.08, 0.15]
	Unpredictability	0.12*	[0.01, 0.24]
	Condition × Unpredictability	0.01	[-0.11, 0.12]
Win-Stay			
	Condition	0	[-0.12, 0.11]
	Unpredictability	-0.12*	[-0.23, -0.01]
	Condition × Unpredictability	0.05	[-0.07, 0.16]

Note: All estimates are standardized beta weights with corresponding 95% confidence intervals.
* $p < .05$, ** $p < .01$, *** $p < .001$

Table 3. Correlations and descriptive statistics for all variables in Experiment 2.

Variable	**1**	**2**	**3**	**4**	**5**	**6**
Correlations						
1. Correct	-					
2. Perseveration	-0.82**	-				
3. Lose-Shift	0.24**	-0.64**	-			
4. Win-Stay	0.68**	-0.32**	0.03	-		
5. Child Unpredictability	-0.02	-0.01	0.03	-0.06	-	
6. Child SES	0.06	-0.09	0.07	0.05	-0.34**	-
Descriptive Statistics						
N	325	325	325	325	325	325
Mean	0.62	0.21	0.58	0.83	1.76	5.45
SD	0.1	0.08	0.17	0.15	1.05	1.16
Min	0.39	0.03	0.07	0.38	1	1.6
Max	0.9	0.46	1	1	6.5	7

Note: * $p < .05$, ** $p < .01$, *** $p < .001$

Table 4. Multilevel regression results for Experiment 2.

Model	Term	β	95% CI
Correct			
	Condition	0.05	[-0.02, 0.12]
	Unpredictability	-0.01	[-0.08, 0.06]
	Trial Type	-0.38***	[-0.45, -0.31]
	Condition × Unpredictability	0.03	[-0.04, 0.1]
	Condition × Trial Type	0	[-0.07, 0.07]
	Unpredictability × Trial Type	-0.02	[-0.09, 0.05]
	Condition × Unpredictability × Trial Type	0.01	[-0.06, 0.09]
Perseveration			
	Condition	-0.04	[-0.11, 0.03]
	Unpredictability	-0.01	[-0.08, 0.06]
	Trial Type	0.42***	[0.35, 0.49]
	Condition × Unpredictability	-0.04	[-0.11, 0.03]
	Condition × Trial Type	0	[-0.07, 0.07]
	Unpredictability × Trial Type	0.02	[-0.05, 0.09]
	Condition × Unpredictability × Trial Type	0	[-0.07, 0.07]
Lose-Shift			
	Condition	0	[-0.1, 0.1]
	Unpredictability	0.04	[-0.06, 0.14]
	Trial Type	-0.09***	[-0.13, -0.05]
	Condition × Unpredictability	0.05	[-0.05, 0.15]
	Condition × Trial Type	-0.02	[-0.07, 0.02]
	Unpredictability × Trial Type	-0.01	[-0.06, 0.03]
	Condition × Unpredictability × Trial Type	-0.04†	[-0.08, 0]
Win-Stay			
	Condition	0.04	[-0.06, 0.14]
	Unpredictability	-0.05	[-0.15, 0.04]
	Trial Type	-0.07**	[-0.12, -0.03]
	Condition × Unpredictability	-0.03	[-0.13, 0.07]
	Condition × Trial Type	0.01	[-0.04, 0.05]
	Unpredictability × Trial Type	0	[-0.04, 0.05]
	Condition × Unpredictability × Trial Type	0.02	[-0.03, 0.06]

Note: All estimates are standardized beta weights with corresponding 95% confidence intervals.
* $p < .05$, ** $p < .01$, *** $p < .001$

Table 5. Correlations and descriptive statistics for all variables in Experiment 3.

Variable	1	2	3	4	5	6
Correlations						
1. Correct	-					
2. Perseveration	-0.89**	-				
3. Lose-Shift	0.22**	-0.53**	-			
4. Win-Stay	0.56**	-0.16**	-0.23**	-		
5. Child Unpredictability	-0.14*	0.12*	-0.03	-0.05	-	
6. Child SES	0.11*	-0.09	0.06	0.1	-0.21**	-
Descriptive Statistics						
N	348	348	348	348	348	348
Mean	0.7	0.17	0.47	0.89	2.01	4.37
SD	0.11	0.1	0.17	0.13	1.25	0.46
Min	0.07	0.03	0	0.42	1	2.2
Max	0.9	0.91	1	1	6.62	5.6

Note: * $p < .05$, ** $p < .01$, *** $p < .001$

Table 6. Multilevel regression results for Experiment 3.

Model	Term	β	95% CI
Correct			
	Condition	-0.12*	[-0.22, -0.02]
	Unpredictability	-0.16**	[-0.26, -0.06]
	Trial Type	-0.27***	[-0.32, -0.22]
	Trial Type^2	0.29***	[0.25, 0.34]
	Condition × Unpredictability	-0.09†	[-0.19, 0.01]
	Condition × Trial Type	0.01	[-0.04, 0.05]
	Unpredictability × Trial Type	-0.02	[-0.07, 0.02]
	Condition × Trial Type^2	0.05	[-0.03, 0.13]
	Unpredictability × Trial Type^2	0.03	[-0.05, 0.1]
	Condition × Unpredictability × Trial Type	-0.03	[-0.08, 0.02]
	Condition × Unpredictability × Trial Type^2	0.01	[-0.07, 0.09]
Perseveration			
	Condition	0.09†	[-0.01, 0.19]
	Unpredictability	0.16**	[0.06, 0.26]
	Trial Type	0.26***	[0.21, 0.3]
	Trial Type^2	-0.28***	[-0.33, -0.24]
	Condition × Unpredictability	0.07	[-0.03, 0.17]
	Condition × Trial Type	-0.02	[-0.06, 0.03]
	Unpredictability × Trial Type	0	[-0.04, 0.05]
	Condition × Trial Type^2	-0.06	[-0.13, 0.02]
	Unpredictability × Trial Type^2	-0.07†	[-0.15, 0.01]
	Condition × Unpredictability × Trial Type	0.01	[-0.04, 0.06]
	Condition × Unpredictability × Trial Type^2	-0.03	[-0.11, 0.05]
Lose-Shift			
	Condition	-0.01	[-0.12, 0.09]
	Unpredictability	-0.07	[-0.17, 0.04]
	Trial Type	-0.01	[-0.05, 0.04]
	Trial Type^2	0.05*	[0.01, 0.1]
	Condition × Unpredictability	0.04	[-0.07, 0.14]
	Condition × Trial Type	0.04	[-0.01, 0.08]
	Unpredictability × Trial Type	-0.01	[-0.06, 0.04]
	Condition × Trial Type^2	0	[-0.08, 0.07]
	Unpredictability × Trial Type^2	0.09*	[0.01, 0.17]

	Condition × Unpredictability × Trial Type	-0.01	[-0.06, 0.03]
	Condition × Unpredictability × Trial Type^2	-0.01	[-0.09, 0.06]
Win-Stay			
	Condition	-0.15*	[-0.26, -0.03]
	Unpredictability	-0.11†	[-0.22, 0.01]
	Trial Type	-0.03	[-0.06, 0.01]
	Trial Type^2	0.04*	[0, 0.08]
	Condition × Unpredictability	-0.09	[-0.2, 0.03]
	Condition × Trial Type	-0.01	[-0.04, 0.03]
	Unpredictability × Trial Type	-0.03	[-0.07, 0.01]
	Condition × Trial Type^2	0.03	[-0.03, 0.1]
	Unpredictability × Trial Type^2	0.02	[-0.05, 0.08]
	Condition × Unpredictability × Trial Type	-0.02	[-0.06, 0.02]
	Condition × Unpredictability × Trial Type^2	0	[-0.07, 0.06]

Note: All estimates are standardized beta weights with corresponding 95% confidence intervals.
* $p < .05$, ** $p < .01$, *** $p < .001$

Table 7. Correlations and descriptive statistics for all variables in Experiment 4.

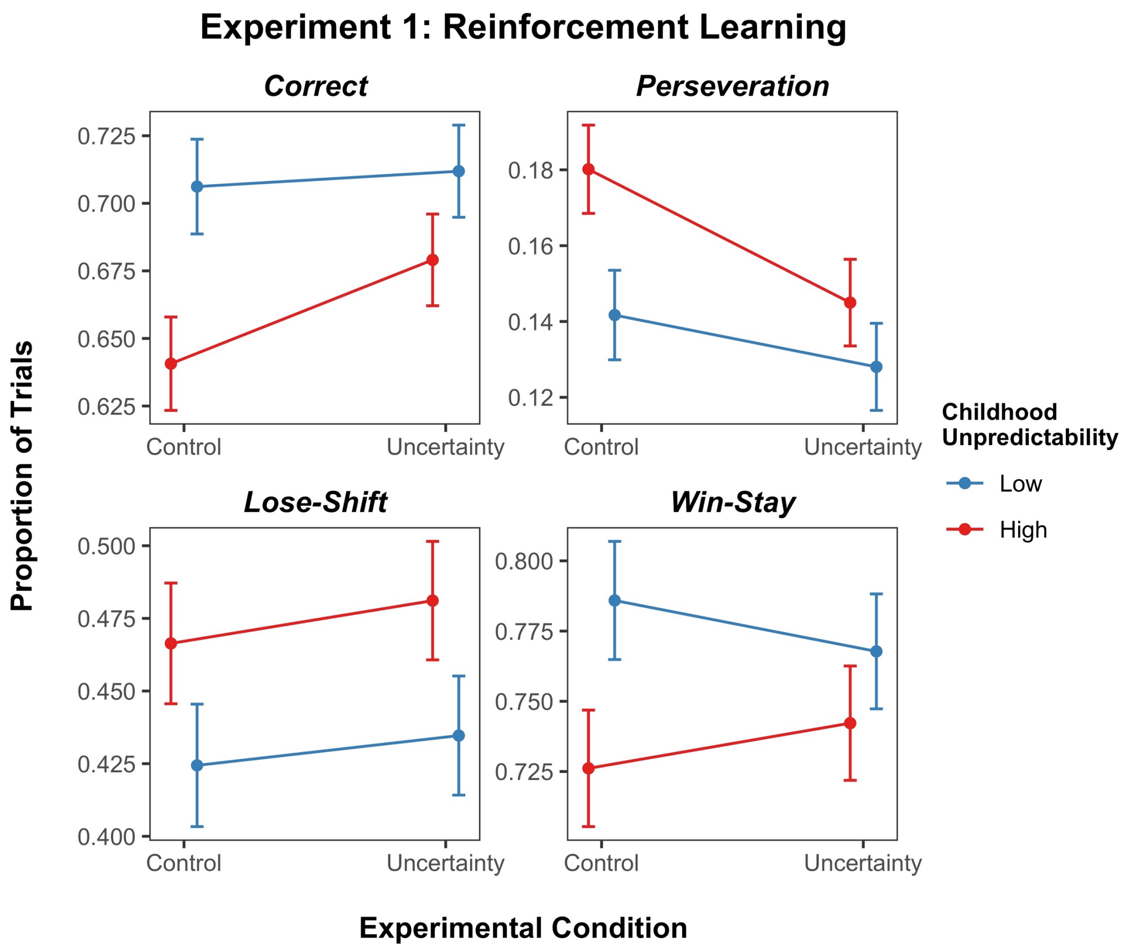
Variable	**1**	**2**	**3**	**4**	**5**	**6**
Correlations						
1. Correct	-					
2. Perseveration	-0.88**	-				
3. Lose-Shift	0.51**	-0.74**	-			
4. Win-Stay	0.5**	-0.15*	0.06	-		
5. Child Unpredictability	-0.02	-0.03	0.03	-0.09	-	
6. Child SES	-0.06	0.1	-0.11	0.02	-0.39**	-
Descriptive Statistics						
N	269	269	269	269	269	269
Mean	0.56	0.23	0.54	0.74	1.92	5.53
SD	0.08	0.08	0.14	0.15	1.16	1.15
Min	0.4	0.02	0.12	0.39	1	1
Max	0.79	0.45	0.97	1	7	7

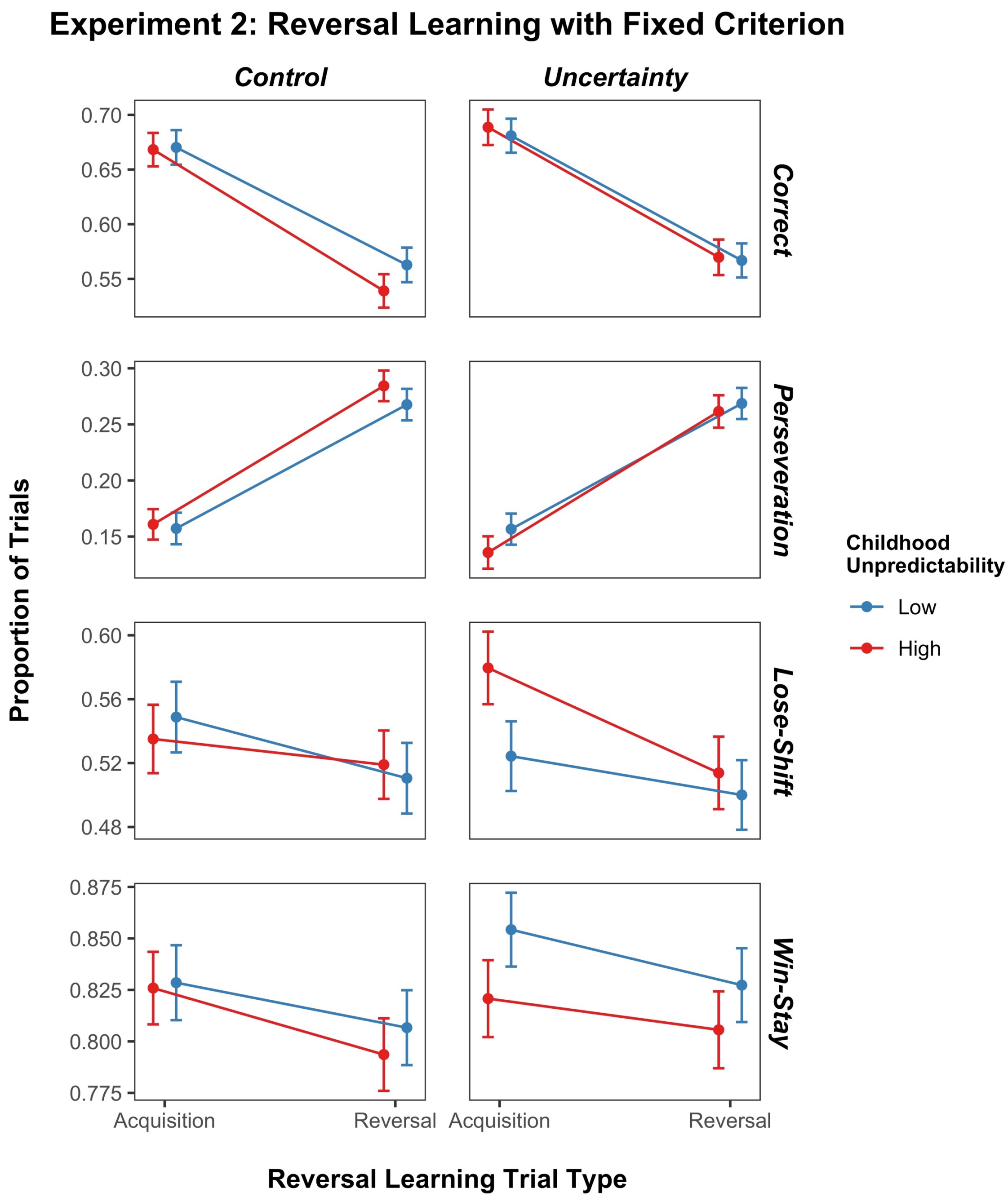
Note: * $p < .05$, ** $p < .01$, *** $p < .001$

Table 8. Multilevel regression results for Experiment 4.

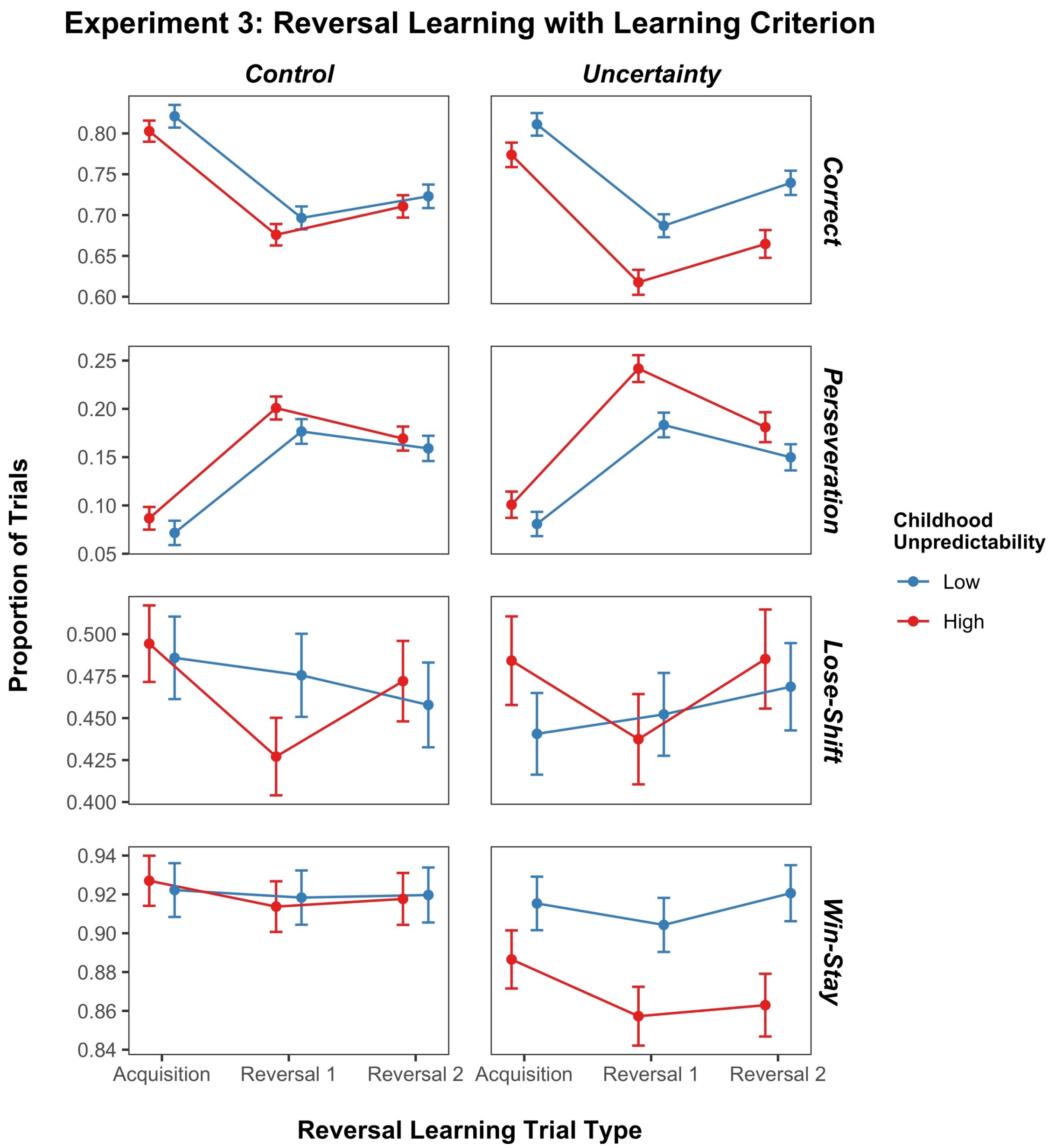
Model	**Term**	**β**	**95% CI**
Correct			
	Condition	0	[-0.04, 0.04]
	Unpredictability	-0.01	[-0.05, 0.03]
	Trial Type	-0.1***	[-0.14, -0.06]
	Trial Type^2	0.13***	[0.08, 0.17]
	Condition × Unpredictability	-0.01	[-0.05, 0.04]
Perseveration			
	Condition	-0.01	[-0.06, 0.04]
	Unpredictability	-0.01	[-0.06, 0.04]
	Trial Type	0.08***	[0.04, 0.12]
	Trial Type^2	-0.11***	[-0.15, -0.07]
	Condition × Unpredictability	0	[-0.05, 0.05]
Lose-Shift			
	Condition	0.02	[-0.06, 0.09]
	Unpredictability	0	[-0.07, 0.07]
	Trial Type	0.03†	[0, 0.07]
	Trial Type^2	0.03†	[0, 0.07]
	Condition × Unpredictability	-0.02	[-0.09, 0.05]
Win-Stay			
	Condition	-0.01	[-0.09, 0.06]
	Unpredictability	-0.07†	[-0.15, 0.01]
	Trial Type	-0.1***	[-0.13, -0.06]
	Trial Type^2	0.08***	[0.04, 0.11]
	Condition × Unpredictability	-0.04	[-0.12, 0.04]

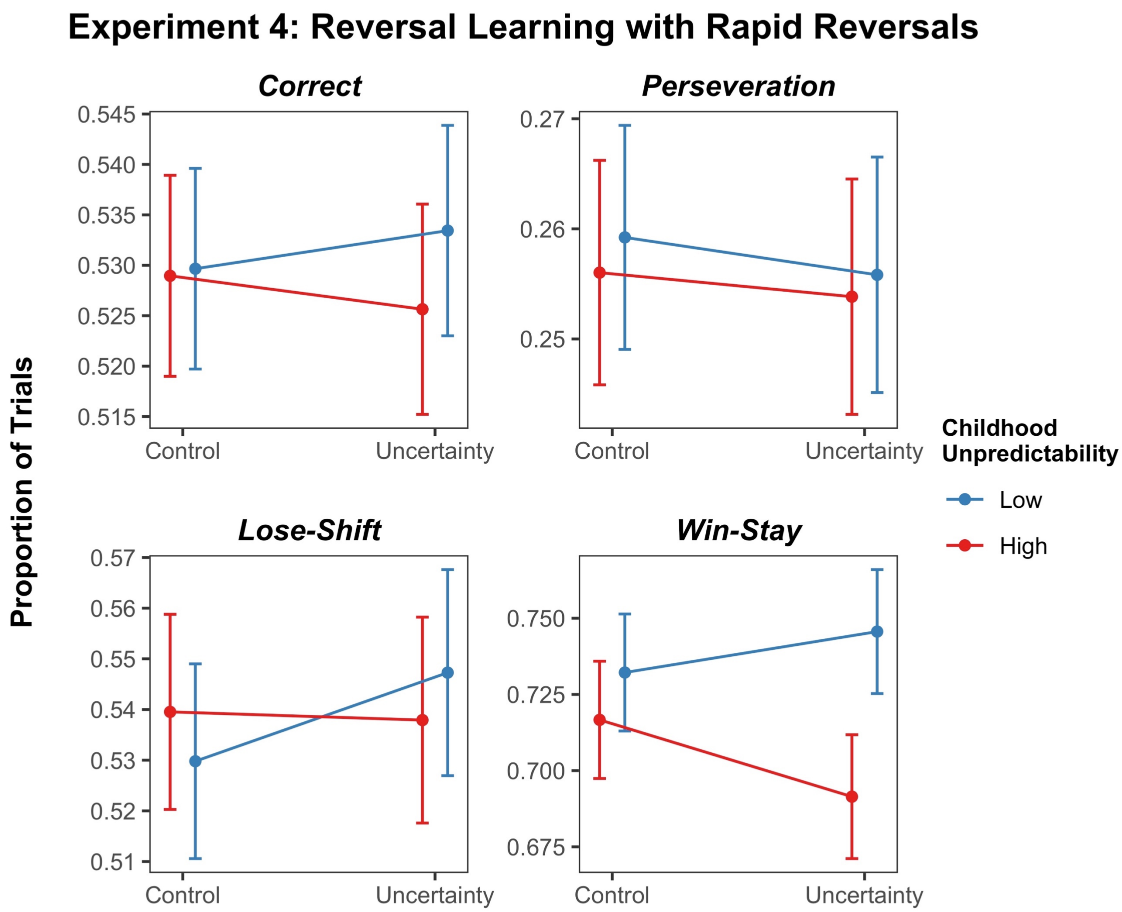
Note: All estimates are standardized beta weights with corresponding 95% confidence intervals.
* $p < .05$, ** $p < .01$, *** $p < .001$


Experiment 1: Reinforcement Learning
Correct
Perseveration
Lose-Shift
Win-Stay
Proportion of Trials
0.725
0.700
0.675
0.650
0.625
0.18
0.16
0.14
0.12
0.500
0.475
0.450
0.425
0.400
0.800
0.775
0.750
0.725
Control
Uncertainty
Childhood
Unpredictability
Low
High
Experimental Condition



Experiment 2: Reversal Learning with Fixed Criterion
Control
Uncertainty
Correct
Perseveration
Lose-Shift
Win-Stay
Proportion of Trials
Reversal Learning Trial Type
Acquisition
Reversal
Childhood Unpredictability
Low
High
0.70
0.65
0.60
0.55
0.30
0.25
0.20
0.15
0.60
0.56
0.52
0.48
0.875
0.850
0.825
0.800
0.775


Experiment 3: Reversal Learning with Learning Criterion
Control
Uncertainty
Correct
Perseveration
Lose-Shift
Win-Stay
Proportion of Trials
0.80
0.75
0.70
0.65
0.60
0.25
0.20
0.15
0.10
0.05
0.500
0.475
0.450
0.425
0.400
0.94
0.92
0.90
0.88
0.86
0.84
Acquisition
Reversal 1
Reversal 2
Reversal Learning Trial Type
Childhood Unpredictability
Low
High



Experiment 4: Reversal Learning with Rapid Reversals
Correct
Perseveration
Lose-Shift
Win-Stay
Proportion of Trials
0.545
0.540
0.535
0.530
0.525
0.520
0.515
0.27
0.26
0.25
0.57
0.56
0.55
0.54
0.53
0.52
0.51
0.750
0.725
0.700
0.675
Control
Uncertainty
Childhood Unpredictability
Low
High

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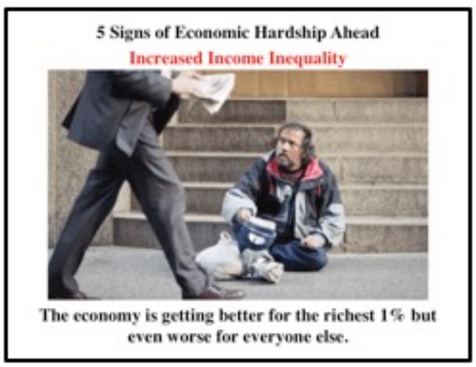
Appendix A

Uncertainty Slideshow

Beginning Slide

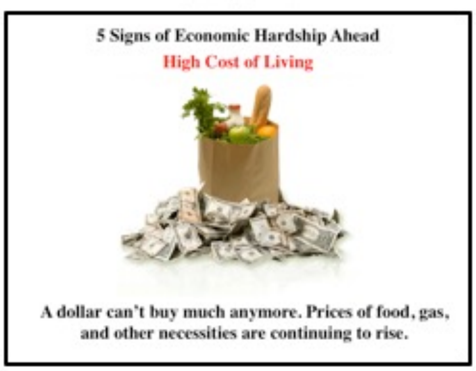
Slide 1

Slide 2



Slide 3

Slide 4



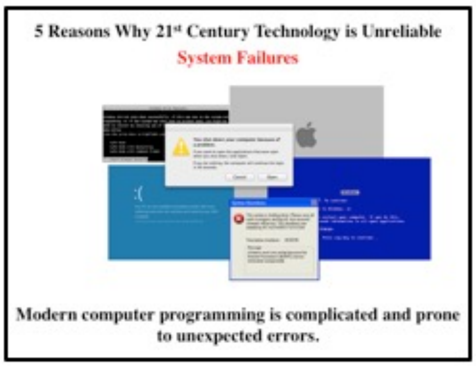
Slide 5

Control Slideshow

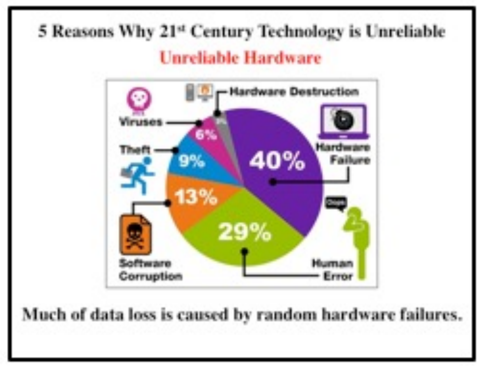
Beginning Slide

Slide 1

Slide 2



Slide 3



Slide 4

Slide 5

Appendix B

Childhood unpredictability items (Young et al., 2018):

Please rate how much each statement describes you and your family in your early childhood from 1 (*not at all*) to 7 (*extremely*).

- My family life was generally inconsistent and unpredictable from day-to-day.
- My parent(s) frequently had arguments or fights with each other or other people in my childhood.
- My parents had a difficult divorce or separation during this time.
- People often moved in and out of my house on a pretty random basis.
- When I woke up, I often didn’t know what could happen in my house that day.
- My family environment was often tense and “on edge”.
- Things were often chaotic in my house.
- I had a hard time knowing what my parent(s) or other people in my house were going to say.